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Bankruptcy prediction in firms with statistical and intelligent techniques and a comparison of evolutionary computation approaches

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ABSTRACT

In this paper, we compare some traditional statistical methods for predicting financial distress to some more "unconventional" methods, such as decision tree classification, neural networks, and evolutionary computation techniques, using data collected from 200 Taiwan Stock Exchange Corporation (TSEC) listed companies. Empirical experiments were conducted using a total of 42 ratios including 33 financial, 8 non-financial and 1 combined macroeconomic index, using principle component analysis (PCA) to extract suitable variables.

This paper makes four critical contributions: (1) with nearly 80% fewer financial ratios by the PCA method, the prediction performance is still able to provide highly-accurate forecasts of financial bankruptcy; (2) we show that traditional statistical methods are better able to handle large datasets without sacrificing prediction performance, while intelligent techniques achieve better performance with smaller datasets and would be adversely affected by huge datasets; (3) empirical results show that C5.0 and CART provide the best prediction performance for imminent bankruptcies; and (4) Support Vector Machines (SVMs) with evolutionary computation provide a good balance of high-accuracy short- and long-term performance predictions for healthy and distressed firms. Therefore, the experimental results show that the Particle Swarm Optimization (PSO) integrated with SVM (PSO–SVM) approach could be considered for predicting potential financial distress.

1. Introduction

Methods for predicting bankruptcy of financial firms became an important issue in the 1960s and have been widely investigated since [1]. Increased emphasis on this topic could be taken as an indicator of the degree of development and robustness of a given country's economy [2]. The high individual, economic, and social costs inherent in corporate failures or bankruptcies have prompted efforts to provide better insight into and prediction of bankruptcy events [3]. Given the radical change of globalization, more accurate forecasting of corporate financial distress would provide useful information for decision-makers, such as stockholders, creditors, governmental officials, and even the general public. In fact, corporate bankruptcies can be caused by many factors such as wrong investment decisions, a poor investment environment, low cash flow and so on [1,4,5]. Therefore, the many current methods for predicting corporate failure must be continuously improved.

Bankruptcy prediction models can be classified into two broad categories: statistical and artificial intelligent (AI) techniques. Beaver [6] pioneered the statistical methods, followed by Altman [1] who applied multi-discriminant analysis (MDA), and also developed stochastic models such as logit [5] and probit [7]. However the practical application of statistical

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methods is limited by their inherent strict assumptions such as linearity, normality, independence among predictor variables and pre-existing functional forms relating to the criterion variable and the predictor variable [8]. Over the past decade, a number of studies have applied artificial intelligent techniques to bankruptcy prediction. Currently, these techniques include (i) decision trees including Interactive Dichotomiser 3 (ID3) [9], C5.0 [10] and classification and regression tree (CART) [11]; (ii) different artificial neural network (ANN) architectures including multi-layer perception (MLP) [12], self-organizing map (SOM) [13] and learning vector quantization (LVQ) [14], (iii) evolutionary approaches including genetic algorithms (GA) [15] and a newer evolutionary technique – particle swarm optimization (PSO); and (iv) other intelligent techniques including Support Vector Machines (SVMs) [8].

Among the intelligent techniques, decision trees form a part of 'machine learning' which is an important area of artificial intelligence [16]. Most decision tree algorithms are used for solving classification problems. Decision trees could be used as a partitioning method to induce the rules of a given dataset and act as a prediction model for future datasets applying the recursive partitioning algorithm (RPA) for predicting bankruptcy in firms proposed by Marais et al. [17]. Frydman et al. [18] applied RPA to bankruptcy prediction and compared it with the MDA. Cho et al. [19] also compared decision trees and case-based reasoning for bankruptcy prediction. C5.0 is a new decision tree algorithm developed based on C4.5 by Quinlan [20]. It includes all functionality of C4.5 and applies the boosting technology for improved accuracy in sample identification. In the ANN approach, MLP has extensive applications in financial services. Since SOM and LVQ are not often used in the financial domain, we investigate the bankruptcy prediction performance of both models. In the evolutionary approach, GA and PSO can enhance the capability and probability of finding global optima and optimizing parameters in the results. Recently, SVM has been used in financial prediction applications such as credit ratings, time series predictions and the detection of insurance claim fraud [21]. Therefore, the purpose of this paper is to compare these various classification techniques to predict financial distress.

In this research, the comparison models use the linear discriminant analysis (LDA), logistic regression (LR), C5.0, CART, SOM, LVQ, SOM, GA, and PSO techniques. The main objectives of this paper are to (1) construct financial distress prediction models from classification techniques, (2) increase the accuracy of these models using financial, non-financial, and macroeconomic ratios, (3) compare the accuracy of traditional statistical, intelligent, and evolutionary computation approaches, and (4) expand these models to form a financial distress prediction system to provide information to investors and monitoring organizations. The data employed in our study was collected from Taiwan Stock Exchange Corporation (TSEC) databases.

The rest of the paper is organized as follows: Section 2 reviews the literature on the comparative analysis of statistical, intelligent, and evolutionary computation approaches. Section 3 provides a brief description of the data organization and the research model. Section 4 presents research results and analysis. Section 5 presents our conclusions.

2. Literature review

We are now going to provide a glimpse into the literature concerning the main statistical and soft computing techniques that so far have been used to analyze distress situations and the bankruptcy prediction problem. In particular, we will focus on LDA, LR, C5.0, CART, SOM, LVQ, SVM, GA–SVM, PSO–SVM techniques and brief details of each of the techniques in this section.

2.1. Statistical techniques

Discriminant analysis (DA) is commonly used to classify a set of observations into predefined classes. Cambell [22] and Fung [23] suggested a diagnostic method in LDA for detecting the possible influential observations based on the influence function. LDA is a classification method which assumes that data in each class are Gaussian-distributed and that there is a unique covariance matrix for each class. LDA also maps the data in a transformed space formed by the eigenvectors of the pooled covariance matrix. Hence a new instance can be classified simply by mapping it in the transformed space and assigning the class of the closest centroid, a process known as linear decision boundaries. However, LDA has some pitfalls. First, linear decision boundaries are inadequate to deal with the Small Sample Size (S3) problem which occurs when the total number of training samples is smaller than the dimensionality of the feature vector. In this situation, the within-class scatter matrix becomes singular; it becomes impossible for LDA to handle the linear decision boundaries. Second, using a single class prototype may prove insufficient and, several prototypes are more appropriate in many situations. Third, we may have too many correlated predictors. Given these issues, we have replaced discriminant analysis with LR, which is much more flexible in its assumptions.

LR is a regression method for predicting a dichotomous dependent variable. Unlike LDA, LR does not require that independent variables be normally distributed or linearly related, nor does it require equal variance within each group [24]. In LR models, the dependent variable is always in categorical form and has two or more levels. Independent variables may be in numerical or categorical form. Recently, many researchers have applied LR to predict financial bankruptcies. Laitinen and Laitinen [25] used Taylor's model in bankruptcy prediction and evaluated the application of the LR model to data from the Compustat database. Premachandra et al. [26] found that LE outperformed data envelopment analysis (DEA) in predicting corporate bankruptcies. LDA and LR are useful for benchmarking other techniques, and are included in our experiment.

2.2. Intelligent techniques

A decision tree (DT) is a non-linear discrimination method which uses a set of independent variables to split a sample into progressively smaller subgroups. The procedure is iterative at each branch in the tree; it selects the independent variable that has the strongest association with the dependent variable according to a specific criterion [27]. The DT analysis model's major algorithms include C5.0 and CART. The C4.5 algorithm improves ID3 with regard to the splitting rule and the calculation method [16]. Rather than entropy measures, it uses the gain-ratio index as a measurement method to segment attributes and is thus less influenced by the ID3 drawback that segmentation nodes prefer too many sub-trees. The C5.0 algorithm is a commercial version of C4.5 with improved rule generation, and is marketed as Clementine and RuleQuest [20]. The boosting method also makes the C5.0 algorithm faster and more memory efficient than C4.5. Boosting is a method for improving the results of machine learning classification algorithms. It sets weight for each sample and, the higher the weight, the greater the sample's influence on the decision tree. Initially, every sample has the same weight. In each trial, a new decision tree is constructed. The weight of each sample is adjusted, such that the learner focuses on samples which are misclassified by the decision tree constructed in the last trial, thus increasing the weight of these samples and thus providing the C5.0 algorithm with improved classification capability.

CART uses tree-building algorithms which are a set of if-then conditions for prediction or case classification [28]. In CART, the tree classifier is built by recursively splitting the instance space into smaller subparts. The CART algorithm generates a binary decision tree, unlike ID3 which only creates two children. CART provides a set of rules that can be used with an unclassified dataset to predict which records will have a given result. Decision tree-based models, such as CART, have a significant advantage in that DT-based models are scalable to large problems and can handle smaller datasets better than ANN models do [29]. Therefore, our study includes a comparison of these two decision tree algorithms to provide suitable suggestions for the prediction of financial bankruptcy.

Unlike the above classification algorithms, the clustering method can be considered to solve the bankruptcy prediction problem. The SOM algorithm was originally introduced by Kohonen [30,31] and is a clustering type of neural network in the sense that it constructs a topology-preserving map of the training data where the location of a unit carries semantic information. For this reason, the main application of this algorithm is the clustering of data. With the SOM, a two-dimensional display of the input space is obtained which naturally lends itself to clear visualization. Practical applications of the SOM can be found in exploratory data analysis, pattern recognition, speech analysis, robotics, industrial and medical diagnostics, instrumentation and control, and hundreds of other tasks. However, little related research focuses on financial distress prediction. Therefore, this research will use the SOM technique to predict healthy as well as bankrupt-prone companies.

Another neural classifier based on competitive supervised learning is the LVQ algorithm [32] which is notable for its heuristic simplicity and its direct adaptation to classification tasks. The LVQ neural architecture does not include a layer of hidden units, so the neural network simply consists only of one input layer and one output layer. In the LVQ algorithm, weight vectors associated with each output unit are known as codebook vectors. The LVQ algorithm is a competitive network, and thus, for each training vector output units compete among themselves to find the winner according to some metric. If the classification is correct, the codebook vector of the closest node is moved toward the training vector; if it is incorrect, it is moved away from the training vector. The LVQ algorithm uses the Euclidean distance to find the winning unit, which modifies its weights using the LVQ learning rule. In generally, LVQ is better than SOM in classification predictions due to supervised learning [31]. However, the application of the LVQ algorithm to financial bankruptcy classification has not been sufficiently explored and this research therefore extends the SOM and LVQ techniques to construct financial prediction models for both healthy and distressed companies.

The optimization problem can be very difficult to solve given huge search parameters, but GA is usually used to search for a function's global optimum, and can also be used to increase the robustness and global optimization of many applications [33]. The GA performs the optimization process in four phases: initialization, selection, crossover, and mutation [34]. In the initialization phase, the search space of all possible solutions is mapped onto a set of finite strings. Each string (called a chromosome) has a corresponding point in the search space. The algorithm starts with the initial solutions selected from a set of configurations in the search space called *population* using randomly generated solutions or by applying special algorithms. Each of the initial solutions is evaluated using a user-defined fitness function. A *fitness* function exists to numerically encode the performance of the chromosome. In the selection phase, a set of individuals with high scores in the fitness function is selected to reproduce itself. This set generates progeny by applying different genetic operators (i.e., crossover or mutation). In the crossover phase, it operates by swapping corresponding segments of a string representation of a couple of chromosomes (called "parents") to produce two chromosomes (called "children"). In the mutation phase, it operates on a single chromosome and one element is chosen at random from the chain of symbols, and the bit string representation is changed with another one. The drawbacks of GA are that the chromosomes from a few comparatively well-fitting (but not optimal) individuals may rapidly come to dominate the population, causing it to converge on a local maximum. Once the population has converged, the ability of the GA to continue to search for better solutions is effectively eliminated.

Another optimization technique is the PSO algorithm, first introduced by Eberhart and Kennedy [35]. PSO incorporates swarming behaviors observed in bird flocks, bee swarms, and even human social behavior. Like evolutionary algorithms, PSO executes searches using a population (called a *swarm*) of individuals (called *particles*) that are updated from iteration to iteration. Each particle has an associated fitness value. These particles move through the search space with a specified velocity in search of an optimal solution. The PSO algorithm searches for the optimal value by sharing historical information and social information between the individual particles [36]. A particle represents a potential problem solution move through a d-dimensional search space. Each particle i represents a candidate position, remembering the best value and the current position which had resulted in that value, called *pbest*. When a particle takes the entire population as its topological neighbors, the best value is a global best and is called *gbest*. PSO has two primary operators: Velocity update and Position update. During each generation, each particle is accelerated toward the *gbest* and its own *pbest*. Different from GA, PSO is easy to implement, has few parameters requiring adjustment, and converges quickly. Therefore, we will integrate these two evolutionary computation techniques with the SVM model.

Support Vector Machine (SVM) was recently developed by Vapnik and his colleagues as a state-of-the-art machine learning algorithm for classifying high-dimensional data [37]. SVM uses a linear model to implement nonlinear class boundaries by mapping input vectors nonlinearly into a high-dimensional feature space [38]. SVM has also been shown to be very resistant to the over-fitting problem, eventually achieving high-generalization performance in solving various time series forecasting and classification problems [34]. Training SVM is equivalent to solving a linearly-constrained quadratic programming problem so that the SVM solution is always unique and globally optimal, unlike the training of other networks which requires non-linear optimization which carries the risk of getting stuck into local minima [39]. Different kernel functions can be selected to obtain the optimal classification results for different classification problems [40]. Kernel functions can provide a simple bridge from linearity to non-linearity for algorithms and a number of kernels can be used in SVM models. These include the linear, polynomial, sigmoid kernel and radial basis functions (RBF). The polynomial kernel function is a non-stationary kernel and is well suited for problems where all the training data is normalized. Moreover, the RBF kernel function has some advantages due to its localized and finite responses across the entire range of real data. In most cases, the polynomial and RBF kernel functions are used in the SVM model.

Since most real world problems are multi-criteria problems, it would seem appropriate to use multi-objective algorithms in seeking solutions. Therefore, this paper aims to effectively deal with continuous financial datasets including Taiwanese listed firms. This research integrates the PSO algorithm with the SVM classification model. The proposed PSO–SVM algorithm can reduce the probability of being trapped in local optima and enhance accuracy and global search capabilities. First, the PSO–SVM algorithm initializes the particles and sets the PSO parameters including the feature mask, C, and γ. The PSO parameter set for the fitness calculation includes the number of iterations, velocity limitation, number of particles, particle dimensions, and weight. Second, the training process is then performed through with the iteration counter initially set to 0. Third, the SVM model is built from the training set, the testing dataset is used to calculate the model's accuracy and fitness value. If the particle's fitness is better than its previous best result (i.e. *pbest)*, the previous best result of the particle is updated accordingly. Furthermore, if the particle's fitness is better than the global best fitness (i.e. *gbest*), the global best fitness is also updated. If the termination criteria are met, then the process ends; otherwise, the next iteration occurs. Finally, with the termination of the training iteration, the PSO will obtain the best values for the SVM parameters, including the feature mask, C, and γ. In addition, the experimental results would also obtain testing accuracy on the testing dataset via the trained SVM classifier.

3. Research methodology and materials

3.1. Data

Our sample included raw data from 200 TSEC-listed firms with an eleven year sampling period from January 2000 to December 2010. The ratio of bankrupt to healthy companies is approximately 1:3 to provide better verification results [41,5]. For bankrupt firms, we gathered financial ratios for the two years prior to bankruptcy. All companies were then divided into a training set and a testing set, with a distribution ratio near 2:1 [42]. In addition, we used the Z-value normalization method to standardize the financial ratios of all 200 firms whose financial ratios were beyond the range of [0, 1]. All data were extracted from formal financial statements including balance sheets, cash flow statements and income statements taken from the TSEC financial databases, which imply that the findings of this research can be generalized to firms outside of Taiwan. Moreover, the proposed methodology and experimental results could be of use to other stock markets worldwide.

3.2. Variable collection

Variable selection for the input vector was based on prior research in financial distress prediction by Kirkos et al. [1], Spathis et al. [43], Fanning and Cogger [44], Persons [9], Stice [45], Kinney and McDaniel [46], and Altman [47]. Several statistical methods exist for selecting variables for analysis including independent sample t-test, discriminant analysis, logistic regression, decision tree, and factor analysis. However, most previous research has adopted the Altman Z-Score model which integrates a few important financial ratios to arrive at a bankruptcy probability for a company and categorize the ratios as five major types: profitability, liquidity, activity, leverage, and solvency [1]. Therefore, this paper adopted variables taken from prior research found in the Taiwanese Economic Journal (TEJ). We selected 50 variables and added two additional ratio categories: non-financial ratios and macroeconomic ratios. Ratios were chosen on the basis of their frequency in the literature and potential relevancy to the study; in addition a few new ratios were initiated in this research. We then used PCA to extract suitable variables as the inputs for prediction. The details of each ratio type are as follows.

- Profitability ratio: profit from sales and equity, including pretax margin, return on total assets, return on equity, earning per share, and gross margin ratios.
- Liquidity ratio: the extent to which a firm can quickly liquidate assets and cover short term liabilities, including turnover rate of inventory, turnover rate of account receivable, turnover rate of fixed assets, turnover rate of total assets, turnover rate of equity, and turnover rate of working capital ratios.
- Activity ratio: efficiency in converting assets and equity into cash or sales, including debt to assets, times interest earned, book value per share, financial leverage ratio, debt to equity, short term & long term debt to book value ratio, fixed assets to total assets ratio, gross margin to total assets ratio, inventory to total assets ratio, inventory to sales ratio, investment ratio, and current assets to total assets ratios.
- Leverage ratio: change in business size and corporate activities between two specific time points, including pretax margin growth ratio, gross margin growth ratio, and sales growth ratios.
- Solvency ratio: long term ability to manage the financed fund, as distinguished from liquidity ratios, including current ratio, acid test ratio, cash ratio, cash flow ratio, cash flow to long term debt, cash flow to total debt, and cash flow to short term & long term debt ratios.
- Non-financial ratio: dividend payout ratio, price–book ratio, proportion of collateralized shares owned by directors, insider holding ratios, past payment record, industry reputation, firm history, and firm size.
- Macroeconomic ratio: for our experiment, the "Monitoring Index" combines and calculates a firm's monetary aggregates M1B, direct and indirect finance, stock price index, industrial production index, nonagricultural employment, customers-cleared exports, imports of machinery and electrical equipment, manufacturing sales, and wholesale, retail and food service sales.

3.3. Variable selection

To extract suitable variables for prediction inputs, we applied factor analysis for data reduction, and PCA with varimax for rotation (VARIMAX) techniques to maximize the sum of the variances of the squared loadings and investigate how groupings of variables measure the same concept. VARIMAX is the most commonly used rotation. Its goal is to minimize the complexity of the components by increasing large loadings and decreasing small loadings within each component, making it a popular scheme for orthogonal rotation which cleans up the factors as follows: "for each factor, high loadings will result for a few variables; the rest will be near zero [48]". In this research, in order to obtain suitable factors, factor selection is based on Kaiser's criteria [48], the absolute value of the factor loadings is greater than 0.5 and the communality is greater than 0.8 in order to obtain suitable factors. Only factors with eigenvalues greater than 1 were retained. In general, only a small subset of factors is kept for further consideration and the remaining factors are considered as either irrelevant or nonexistent.

We collected 33 financial ratios, 8 non-financial ratios, and 1 "Monitoring Indicator" from the 9 original macroeconomic indices. To reduce dimensionality, we ran a factor analysis to test whether the differences between each of the 42 variables were significant; if not, the variable was considered to be non-informative. Table 1 shows the factor loadings, communality and eigenvalues for each variable, along with variance details. In addition, the total explained variance was 68.199%. Consequently, 13 variables presented high communality values and factor loading and these variables were retained in the input vector, while the remaining 29 variables were discarded. We then used factor analysis to process the experiment a second time. Table 2 shows that 4 variables were discarded with a total explained variance of 84.88%, which was significantly higher than in the first round, and factor analysis could thus not be considered the optimal solution. In Table 3, a third round of factor analysis discarded a single variable with a resulting total explained variance of 87.373%, and a fourth round resulted in no variable exclusion and a total explained variance of 95.826% in Table 4.

After four rounds of factor analysis, 34 variables were discarded and the remaining 8 variables presented higher communality values: gearing ratio, debt to equity ratio, debt equity ratio, return on asset ratio, earnings per share ratio, return on equity ratio, current ratio, and acid-test ratio.

4. Empirical analysis

4.1. Experimental period and performance indices

This process uses financial, non-financial, and macroeconomic ratios to construct a financial distress prediction model following four rounds of factor analysis. The variables are then loaded as the input nodes of each classification algorithm. To ensure stability and prediction accuracy, these experimental parameters were used to investigate the 2, 4, 6, and 8 quarters preceding financial distress. In financial risk prediction, accuracy and error rates are important indicators of the reliability of classification algorithms. For this study, the performance matrix was built using overall accuracy, precision, true positive rate and true negative rate. Table 5 shows the relationship among these performance metrics, and the formula for each metric is as follows.

- Accuracy is the percentage of correctly classified instances. It is one of the most widely used classification performance metrics.

$$\text{Overall accuracy} = \frac{\mathrm{TP} + \mathrm{TN}}{\mathrm{TP} + \mathrm{TN} + \mathrm{FP} + \mathrm{FN}}$$

Table 1
First factor analysis results.

Factors	Variables	Factor loadings	Communality	Eigenvalues	Explained variance
1	Equity per share ratio	0.883	0.722	8.724	22.957
	Return on equity ratio	0.876	0.872		
	Return on asset ratio	0.856	0.842		
	Margin before interest and tax ratio	0.702	0.812		
	Pretax margin growth ratio	0.547	0.407		
2	Current ratio	0.819	0.851	3.755	9.881
	Acid-test ratio	0.810	0.807		
	Times interest earned ratio	0.617	0.628		
	Earnings per share ratio	0.525	0.896		
	Price–book ratio	0.478	0.440		
	Gross operating spread ratio	0.466	0.553		
	Cash ratio	0.447	0.423		
	Cash flow to long term debt ratio	0.408	0.527		
3	Gearing ratio	0.953	0.964	2.848	7.496
	Debt to equity ratio	0.951	0.959		
	Debt equity ratio	0.928	0.956		
	Debt ratio	0.639	0.809		
4	Turnover rate of total assets ratio	0.837	0.776	2.641	6.951
	Turnover rate of equity ratio	0.773	0.768		
	Turnover rate of fixed assets ratio	0.593	0.766		
	Gross margin to total assets ratio	0.555	0.683		
	Current assets to total assets ratio	0.524	0.855		
5	Cash flow ratio	0.874	0.835	2.115	5.565
	Cash flow to total debt ratio	0.861	0.787		
	Dividend payout ratio	0.465	0.444		
	Cash flow to short & long term debt	0.191	0.067		
6	Inventory to total assets ratio	0.872	0.849	1.827	4.807
	Inventory to sales ratio	0.839	0.770		
	Proportion of collateralized shares	0.472	0.408		
	Monitoring	0.371	0.239		
	Industry reputation	0.366	0.384		
	Past payment record	0.347	0.265		
7	Insider holding ratio	0.744	0.600	1.460	3.841
	Investment ratio	0.647	0.724		
	Fixed assets to total assets ratio	0.625	0.767		
	History of firm	0.608	0.644		
	Firm size	0.586	0.608		
8	Turnover rate of inventory ratio	0.809	0.765	1.293	3.402
	Turnover rate of working capital ratio	0.724	0.760		
9	Turnover rate of account receivable	0.672	0.494	1.254	3.300
	Gross operating spread growth ratio	0.581	0.477		
	Sales revenue growth ratio	0.469	0.614		
Total explained variance				68.199	

where TP, TN, FP, and FN respectively represent true positive, true negative, false positive, and false negative. TP is the number of correctly classified positive or abnormal instances. TN is the number of correctly classified negative or normal instances. FP is the number of non-fault-prone instances misclassified as fault-prone. FN is the number of fault-prone instances misclassified as non-fault-prone.

- Precision is the number of classified positive or abnormal instances that actually are positive instances.

$$\text{Precision} = \frac{\text{TP}}{\text{TP} + \text{FP}}.$$

Table 2
Second factor analysis results.

Factors	Variables	Factor loadings	Communality	Eigenvalues	Explained variance
1	Return on asset ratio	0.916	0.894	5.822	44.781
	Return on equity ratio	0.915	0.922		
	Earnings per share ratio	0.911	0.896		
	Margin before interest and tax ratio	0.785	0.683		
2	Gearing ratio	0.967	0.980	2.009	15.451
	Debt to equity ratio	0.966	0.978		
	Debt equity ratio	0.946	0.967		
	Debt ratio	0.647	0.774		
3	Current ratio	0.920	0.919	1.672	12.862
	Acid-test ratio	0.882	0.928		
	Cash flow ratio	0.623	0.513		
4	Current assets to total assets ratio	0.885	0.844	1.532	11.787
	Inventory to total assets ratio	0.823	0.736		
Total explained variance				84.88	

Table 3
Third factor analysis results.

Factors	Variables	Factor loadings	Communality	Eigenvalues	Explained variance
1	Debt to equity ratio	0.971	0.985	4.588	50.977
	Gearing ratio	0.970	0.985		
	Debt equity ratio	0.952	0.969		
2	Return on asset ratio	0.933	0.918	1.785	19.829
	Earnings per share ratio	0.926	0.932		
	Return on equity ratio	0.915	0.919		
3	Acid-test ratio	0.908	0.926	1.491	16.568
	Current ratio	0.884	0.865		
	Current assets to total assets ratio	0.581	0.367		
Total explained variance				87.373	

Table 4
Fourth factor analysis results.

Factors	Variables	Factor loadings	Communality	Eigenvalues	Explained variance
1	Gearing ratio	0.969	0.994	4.559	56.984
	Debt to equity ratio	0.969	0.992		
	Debt equity ratio	0.948	0.975		
2	Return on asset ratio	0.933	0.921	1.708	21.345
	Earnings per share ratio	0.929	0.930		
	Return on equity ratio	0.915	0.920		
3	Current ratio	0.958	0.969	1.400	17.497
	Acid-test ratio	0.946	0.965		
Total explained variance				95.826	

- TP rate measures how well a classifier can recognize abnormal records. It is also referred to as the *sensitivity measure*. A classifier with a higher TP rate is more useful to financial institutions in minimizing their potential investment losses.

$$\text{Sensitivity} = \frac{\text{TP}}{\text{TP} + \text{FN}}.$$

Table 5
The relationship with classification performance metrics.

		Prediction	
		Bankruptcy	Normal
Actually	Bankruptcy	TP	FN
	Normal	FP	TN

Table 6
Classification results.

Algorithms		Overall accuracy				Precision				Sensitivity				Specificity			
		2	4	6	8	2	4	6	8	2	4	6	8	2	4	6	8
Statistical	LDA	75.47	80.81	80.3	82.32	68.75	85.41	84.84	92.68	88	77.35	77.77	76.76	64.28	84.78	83.33	90.76
	LR	79.25	77.78	80.3	78.66	71.87	84.44	85.93	89.02	92	71.69	76.38	73.73	67.85	84.78	85	86.15
DT	C5.0	86.79	81.25	78.79	78.75	78.12	79.06	84.37	86.84	**100**	85	75	73.33	75	77.5	83.33	85.71
	CART	84.91	83.75	78.03	76.87	75.75	82.92	85.24	85.33	**100**	85	72.22	71.11	71.42	82.5	85	84.28
ANN	SOM	90	80	77.5	82.5	94.11	85.57	86.27	94.28	84.21	79.48	68.75	73.33	85.23	82.5	87.5	**94.28**
	LVQ	87.5	82.5	79.16	83.12	85	84.21	**95.34**	94.36	89.47	80	64.06	67.67	85.71	85	**96.42**	**94.28**
Other	SVM	90	87.5	85	84.37	94.11	87.5	89.65	89.15	84.21	87.5	81.25	82.22	**95.23**	87.5	89.28	87.14
Evolutionary	GA–SVM	92.5	91.25	86.66	91.87	94.44	90.24	87.5	93.25	89.47	92.5	87.5	92.22	**95.23**	90	85.71	91.42
	PSO–SVM	**95**	**93.75**	**87.5**	**93.12**	**94.73**	**92.68**	87.3	**94.38**	94.73	**95**	**88.7**	**93.33**	**95.23**	**92.5**	86.20	92.85

- TN rate measures how well a classifier can recognize normal records. It is also referred to as the *specificity measure*.

$$\text{Specificity} = \frac{\text{TN}}{\text{TN} + \text{FP}}.$$

- The F-measure, or effectiveness measure, characterizes the performance of classification in a precision–sensitive space.

$$F\text{-measure} = \frac{2^*\text{Precision}^*\text{Sensitivity}}{\text{Precision} + \text{Sensitivity}}.$$

4.2. Experimental results and comparative study

The overall accuracy, precision, sensitivity, specificity, and F-measure metrics were used to evaluate each algorithm for financial prediction performance by applying all 9 classification methods to the dataset. The best result of a specific performance measure is highlighted in boldface in Table 6.

4.2.1. Overall accuracy for classification algorithms

Table 6 presents three interesting findings. First, the testing data for most of the algorithms trended downward from the previous 2 to 8 quarters, indicating that the more imminent the actual financial distress events, the higher overall accuracy obtained by every algorithm aside from the statistical algorithms. LDA had an estimated overall accuracy rate of 75.47% for the previous 2 quarters but, surprisingly, the accuracy rate improved to 82.32%, and the error rate sharply dropped to 17.68% when measured over the previous 8 quarters, indicating that LDA and LR provide stable prediction capability for short-term and long-term.

Second, the SVM algorithm outperforms the other classifiers (i.e., statistical, decision tree, and ANN algorithms). For example, SVM has an estimated overall accuracy rate of 90%, 87.5%, 85%, and 84.37%, respectively, for the previous 2, 4, 6, and 8 quarters.

Third, the SVM algorithm could be improved through evolutionary approaches, like GA and PSO. Furthermore, the SVM model provides better overall accuracy when integrated with PSO than with GA. In addition, the PSO–SVM model shows the best overall accuracy for the previous 2 to 8 quarters.

4.2.2. Precision measure for classification algorithms

Precision measure is the number of classified positive or abnormal instances that actually are positive instances, and a higher precision measure indicates a reduced likelihood of misclassifying healthy companies as distressed. Table 6 shows statistical and DT algorithms have low precision measures for the previous 2 quarters, but that the precision measures substantially increase with the duration of the period under consideration. Thus we can assume that the statistical and DT algorithms would return high accuracy predictions, though they must review larger datasets to construct the classification models.

On the other hand, the SOM and LVQ algorithms both have high-precision short- and long-term measures. The experimental results found that integrating the evolutionary approach with the SVM model increases the precision measure. For instance, PSO–SVM has better precision measures for the previous 2, 4, and 8 quarters. We could thus assume both neural networks and evolutionary computing could be used to train the model and obtain quickly convergence through smaller dataset (e.g., 2 or 4 quarters).

4.2.3. Sensitivity measure for classification algorithms

With LDA, LR, C5.0, CART, SOM, LVQ, SVM, GA–SVM and PSO–SVM, the respective sensitivity measures for the previous 2 quarters were 88%, 92%, 100%, 100%, 84.21%, 89.47%, 84.21%, 89.47%, and 94.73%. In general, the result shows that the sensitivity measures for the statistical, DT, and ANN algorithms trended poorly from the 2nd to the 8th quarter preceding a financial crisis, showing that the more imminent the crisis is, the higher the sensitivity measure will be. The C5.0 and CART algorithms predict bankruptcies with 100% accuracy within the 2 quarters preceding the bankruptcy, showing that the DT approach has outstanding short-term bankruptcy prediction capabilities.

However, the experimental results found SVM, GA–SVM, and PSO–SVM outperformed other classification algorithms in terms of the average sensitivity measure for predicting bankruptcy, especially over longer periods (i.e., 6 to 8 quarters preceding the crisis). PSO–SVM outperformed the other 8 algorithms for the previous 4, 6, and 8 quarters, showing that PSO–SVM has outstanding short- and long-term bankruptcy prediction capabilities. Thus, the experimental results show that the evolutionary approach could enhance and stabilize the prediction accuracy rate.

4.2.4. Specificity measure for classification algorithms

Specificity measures how well a classifier can recognize normal companies. With LDA, LR, C5.0, CART, SOM, LVQ, SVM, GA–SVM and PSO–SVM, the respective specificity measures for the previous 2 quarters were 64.28%, 67.85%, 75%, 71.42%, 95.23%, 85.71%, 95.23%, 95.23% and 95.23%, while for the previous 8 quarters they were 90.76%, 86.15%, 85.71%, 84.28%, 94.28%, 94.28%, 87.14%, 91.42% and 92.85%. In general, these results show that the specificity measure for the statistical, DT, and ANN algorithms trend best from two to eight quarters preceding the financial crisis. The results thus indicate that additional datasets could improve the accuracy rate for the prediction of normal companies using the statistical, DT, and ANN algorithms.

Similar to the sensitivity measures, we found that the average specificity measure for SVM, GA–SVM, and PSO–SVM was better for predicting normal companies than other classification algorithms, especially in the short term (i.e., 2 and 4 preceding quarters). PSO–SVM was found to outperform the other 8 algorithms for predicting normal companies for the previous 2 and 4 quarters, while LVQ has the best specificity measures for normal company predictions for the previous 6 and 8 quarters. In sum, PSO–SVM provides outstandingly accurate short- and long-term predictions for normal companies. Therefore, the experimental results show that the evolutionary approach could also enhance and stabilize the accuracy rate for normal company predictions.

4.2.5. F-measure for classification algorithms

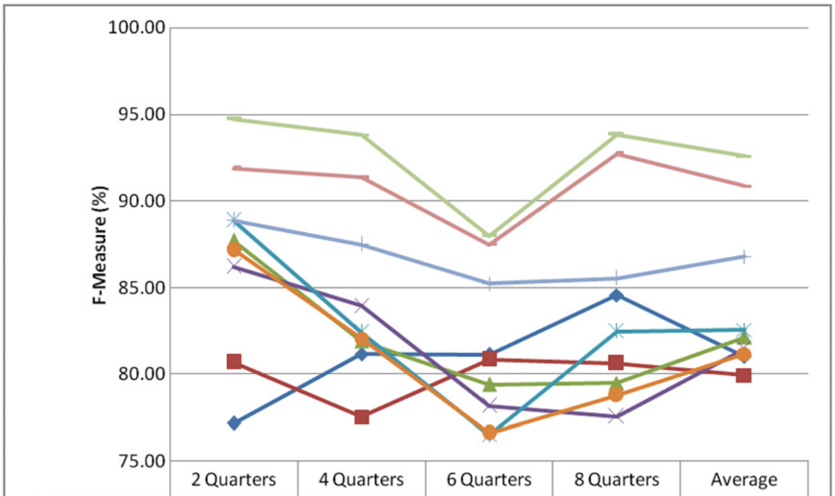
The F-measure combines precision with sensitivity measures and is used to evaluate the overall performance for predictions on bankrupt companies. Fig. 1 shows that LDA outperforms LR in prediction performance, and the experimental results show that LDA trends upward from the 2nd to the 8th quarter preceding the onset of financial crisis. In the DT approach, C5.0 has a better F-measure than the CART algorithm does while, in the ANN approach, SOM has a better F-measure than the LVQ algorithm. Finally, SVM provides better predictions for the previous 2 to 8 quarters than the statistical, DT and ANN algorithms do, and it also maintains stable and high F-measures in both the short- and long-term. The experimental results also show that evolutionary computation outperformed the other classification algorithms in terms of convergence and optimization abilities for integration with the SVM algorithm. In addition, PSO–SVM provides the best prediction performance with its high F-measure in both the short- and long-term.

5. Conclusions

Following experiments with overall accuracy, precision, sensitivity, specificity, and F-measure metrics, we summarize four critical contributions. First, following four rounds of factor analysis, 8 variables with higher communality values were kept while the remaining 34 variables were discarded. But, with nearly 80% fewer financial ratios, our approach is still able to forecast bankruptcy with high accuracy. Furthermore, 8 non-financial ratios and 1 combined macroeconomic index were eliminated by the first PCA analysis due to lower factor loading or communality for bankruptcy prediction. Therefore, our results from 200 TSEC-listed firms show that financial rations have a greater effect on financial prediction performance than non-financial ratios and macroeconomic indices do.

Second, the closer we get to the time of the actual bankruptcy event, the more accuracy predictions will for all classification algorithms except for the LDA and LR algorithms. Traditional statistical methods are better able to handle large datasets without suffering a drop in prediction performance. Additionally, intelligent techniques could help to improve performance with smaller datasets and would be influenced by huge datasets.

Third, experimental results with sensitivity analysis show C5.0 and CART to have the best short-term prediction performance for bankrupt companies. SVM and evolutionary computation could raise long-term prediction performance for bankrupt companies. On the other hand, specificity analysis shows LDA, LR, C5.0 and CART have poor short-term prediction



	2 Quarters	4 Quarters	6 Quarters	8 Quarters	Average
LDA	77.19	81.18	81.15	84.57	81.02
LR	80.69	77.54	80.87	80.65	79.94
C5.0	87.71	81.92	79.40	79.51	82.14
CART	86.20	83.94	78.19	77.57	81.48
SOM	88.88	82.41	76.51	82.49	82.57
LVQ	87.17	82.05	76.63	78.81	81.17
SVM	88.88	87.50	85.24	85.54	86.79
GA-SVM	91.88	91.35	87.50	92.73	90.87
PSO-SVM	94.73	93.82	87.99	93.85	92.60

Fig. 1. The *F*-measure for classification results.

performance for normal companies, and the statistical and DT algorithms provide worse long-term prediction results than the ANN and evolutionary computation algorithms.

Finally, this paper suggests that SVM could be a more suitable method than the traditional statistical, DT and ANN techniques in developing a model for predicting financial distress. The GA and PSO techniques could also be integrated with SVM. Therefore, this paper proposes that the PSO–SVM approach could be considered as a means for predicting potential financial distress.

More research is needed on this topic. While the results of this research were obtained through classification algorithms, other soft-computing methods can also be applied to financial predictions. In addition, our experimental results were obtained from TSEC public datasets. Data from other stock markets or financial statement sources can be tested to verify and extend this approach. Finally, recent studies have demonstrated that different kinds of firms are influenced by different financial ratios, and research could be conducted to verify the utility of relevant financial, non-financial, and macroeconomic ratios using the proposed approach.

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